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ABSTRACT

In this study a six-variable multiple discriminant analysis model was developed that correctly predicted 70% of Moody's bond ratings, 76% of Standard & Poor's, and 81% where both agencies assigned the same bond rating. Fixed charge coverage was found to be the most important financial variable on a univariate basis for determining bond ratings, however, it did a relatively poor job in predicting bond ratings when employed by itself.

AUTHORS

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This research was completed while all three authors were at the University of Missouri-Columbia.

A DISCRIMINANT ANALYSIS OF ELECTRIC UTILITY BOND RATINGS

I. Introduction

Bond ratings, which represent the judgment of informed and sophisticated financial analysts concerning the credit risk of firms, have been the subject of numerous studies [9, 10, 14, 15, 18, 20] in recent years. By constructing statistical models of the bond rating process, insight has been gained concerning the type of information that analysts presumably employ in making their judgments about a firm's credit worthiness. For industrial firms variables related to size, profitability, financial leverage, fixed coverage, risk/earnings instability and subordination have been identified as important determinants of the bond ratings assigned by financial analysts. Using a variety of variables and statistical techniques, models have been developed that correctly classify between 55 and 75 percent of the industrial bonds into their assigned Moody's or Standard and Poor's rating categories. In addition, the information content of bond rating changes has also been examined [7, 8, 16].

In this study a discriminant analysis approach was employed to identify the variables for the electric utility industry that enabled us to best discriminate between bonds in different bond rating categories. The reasons for selecting the electric utility industry for examination were twofold. First, because the electric utility industry is viewed as being relatively homogeneous, financial variables may do a better job of discriminating between bonds in different categories for utilities than for the more heterogeneous industrial grouping. Second, with

the general rise in interest rates, the cost of debt capital has increased for electric utility firms. This has led to greater consideration of debt costs by all parties concerned with regulatory proceedings. Recent testimony in at least two electric utility rate cases (Public Utilities Control Authority of Connecticut Dockets Nos. 760604 and 760605, and Public Utility Commission of Texas Docket No. 178) stressed the need for substantial revenue increases in order to preserve or increase a firm's bond rating. Specifically, it was suggested that if sufficient rate increases were not granted, the firm's fixed coverage ratio would decrease causing the firm's bonds to be downgraded leading to an increase in the effective interest rate; consequently, the company and its consumers would have to pay the increased interest costs. While fixed coverage may be important in the rating process, we are unaware of research suggesting that any single variable captures virtually all of the information informed financial analysts presumably employ when rating public utility bonds. Previous research on electric utility bond ratings [2] does not address this question; in addition, this previous research appears to suffer from certain methodological problems.

The purposes of this study were: (1) to develop a model to predict (or discriminate between) electric utility bonds in different bond rating classifications for both Moody's and Standard & Poor's; (2) to examine the relative importance of the financial variables employed in these models; and (3) to compare the predictive ability of the multiple discriminant analysis model with a univariate model employing the fixed coverage ratio.

II. Methodology

A. Sample Firms

Data for 1970-1975 were gathered on ninety-seven electric utility firms listed on the COMPUSTAT data tapes as of December 31, 1975 that had first mortgage bonds outstanding rated in the top four bond rating classifications by both Moody's and Standard & Poor's. (A list of the ninety-seven firms is available from the authors. Virtually all electric utility firms had their first mortgage bonds rated in the top four categories.) For Moody's the top four categories were Aaa, Aa, A and Baa while for Standard & Poor's they were AAA, AA, A and BBB. Recently, Standard & Poor's further subdivided the AA, A and BBB groups by appending pluses and minus to these ratings; for our purposes we disregard these subdivisions. The number of firms in the top four Moody's categories were Aaa--5, Aa--41, A--32 and Baa--19. For Standard & Poor's there were 3 AAA rated firms, 32 rated AA, 45 A and 17 BBB rated firms.

B. Variables

Based on a thorough review of previous bond rating studies and related work on the predictive ability and interrelationships between financial variables [1, 3, 17, 19], the nineteen variables listed in Exhibit 1 were considered for inclusion in the multiple discriminant model. Seventeen of these variables were financial variables while two, X_1 (Regulatory Climate) and X_{14} (Geographical Area) attempted to measure certain non-financial factors that might influence the bond rating process, and consequently, bond ratings. X_1 was based

EXHIBIT 1

VARIABLE NUMBER AND DESCRIPTION

VARIABLE NUMBER	NAME
X_1	Regulatory Climate*
X_2	Total Assets
X_3	Total Operating Revenue
X_4	Long-Term Debt/Invested Capital
X_5	Debt & Preferred Stock/Total Assets
X_6	Net Income/Total Assets
X_7	Earnings Before Taxes/Total Operating Revenue
X_8	Cash Flow**/Fixed Charges
X_9	Earnings Before Interest & Taxes/Fixed Charges
X_{10}	Cash Flow**/Total Assets
X_{11}	Residential Electric Sales/Total Electric Sales
X_{12}	AFUDC***/Net Income
X_{13}	Construction Expenses/Total Assets
X_{14}	Geographical Area****
X_{15}	Dividend Payout Ratio
X_{16}	1970-1975 Growth Rate in Cash Flow**
X_{17}	1970-1975 Growth Rate in Net Earnings
X_{18}	Standard Deviation of 1970-1975 Cash Flows**
X_{19}	Fuel Expenses/Total Electric Sales

* As determined by White, Weld & Co. (1 = most favorable, 4 = least favorable)

** Cash flow = operating income after taxes + income taxes + depreciation + interest charges - AFUDC

*** AFUDC = Allowance for Funds Used During Construction

**** Federal Power Commission regional breakdown where company supplied a major portion of its electricity.

on a major brokerage firm's assessment [6] of the regulatory climate in the state where the majority of the firm's revenue originated from, while X_{14} indicated the general geographic region in which the firm derived the majority of its sales. (While both of these variables were classificatory variables, available evidence [12] suggests discriminant analysis is robust in such situations.)

Variables X_2 (Total Assets) and X_3 (Total Operating Revenue) measure size; variables related to size have been found to be important in previous bond rating studies. X_4 (Long-Term Debt/Invested Capital) and X_5 (Debt & Preferred Stock/Total Assets) measure financial leverage which has also been found to be important in previous work. Variables X_6 (Net Income/Total Assets), X_7 (Earnings Before Taxes/Total Operating Revenue), and X_{10} (Cash Flow/Total Assets) measure various aspects of profitability, while X_8 (Cash Flow/Fixed Charges) and X_9 (Earnings Before Interest & Taxes/Fixed Charges) measure fixed charge coverage; similar variables have also been important in earlier studies. Variables X_{11} (Residential Electric Sales/Total Electric Sales), X_{12} (Allowance for Funds Used During Construction/Net Income), X_{13} (Construction Expenses/Total Assets) and X_{19} (Fuel Expenses/Total Electric Sales) are all unique to the electric utility industry. X_{15} (Dividend Payout) was included to reflect relative differences in dividend policy, while variables X_{16} (1970-1975 Growth Rate in Cash Flow), X_{17} (1970-1975 Growth Rate in Net Earnings) and X_{18} (Standard Deviation of 1970-1975 Cash Flows) measure various aspects of growth and stability for electric utility firms. In Appendix A the means, standard deviations and univariate F ratios (testing for differences between the means) for all 19 variables

are presented, by bond rating group, for both Moody's and Standard & Poor's. The correlation matrix between all of the variables is presented in Appendix B.

C. Discriminant Analysis

Multiple discriminant analysis is a multivariate statistical technique that allows observations (firms in this study) to be classified into appropriate *a priori* groups (bond ratings) on the basis of a set of independent or predictor variables. While all 19 variables could be employed, this would result in a great deal of "noise" in the discriminant model as Lachenbruch has noted [12, 75]. Complete stepwise procedures were employed to reduce the original 19 variables to a six variable model employing the same variables for both Moody's and Standard & Poor's. (The six variable model was selected after examining a number of models for both Moody's and Standard & Poor's including from four to ten variables. Six variables appeared reasonable based on the relative independence of the variables and the very small incremental increases in discriminatory ability when more than six variables were employed. Slightly better models were obtained for either Moody's or Standard & Poor's; however the reported six variable model was the best for both groups simultaneously.)

Due to the small number of Moody's Aaa bonds (5) and Standard & Poor's AAA bonds (3) it was impossible (employing normal discriminant analysis techniques) to develop a four-group model. Since the number of variables exceeded the number of cases, the dispersion (variance-covariance) matrices for the Aaa and AAA groups were singular. Hence,

we excluded the five Aaa-rated firms for Moody's leaving 92 bonds for analysis. For Standard & Poor's, the 3 AAA-rated firms were excluded leaving 94 bonds rated AA, A or BBB for analysis. In Appendix C an alternative approach was employed (based on assuming the dispersion matrix for the Aaa[AAA] group was equal to the dispersion matrix for the Aa[AA] group) that allowed the four group model to be estimated.

Tests for the equality of the dispersion matrices between the three bond rating groups resulted in the rejection of the null hypothesis of equal dispersion matrices for both Moody's (.045 significance level) and Standard & Poor's (.005 significance level); hence, quadratic as opposed to linear classification rules were employed. Also, because quadratic classification procedures were employed the typical discriminant functions (two in this case) and their coefficients were not reported. (Discriminant functions are not particularly meaningful when quadratic classification rules are employed.) Finally, we employed equal prior probabilities for classification purposes. Ideally the prior probabilities should reflect the distribution of bonds in the population; however, in recent years the number of bonds in different rating categories has been undergoing considerable change. Given this instability in the population prior probabilities, we believed equal prior probabilities were more appropriate and provide results that were more consistent and generalizable. The specific computer program employed for this analysis is described in [4]. (For further elaboration on the mathematical assumptions and difficulties encountered in employing multiple discriminant analysis, see [4, 12, 13]).

III. Empirical Findings

A. Analysis of the variables in the MDA model

The six variables selected by the complete stepwise procedure were: X_1 (Regulatory Climate), X_2 (Total Assets), X_6 (Net Income/Total Assets), X_9 (Earnings Before Interest & Taxes/Fixed Charges), X_{13} (Construction Expenses/Total Assets) and X_{17} (1970-1975 Growth Rate in Net Earnings). An examination of Appendix A indicated that, as expected, the more favorable the Regulatory Climate, X_1, the higher the bond rating. The results indicate that except for the Baa(BBB) group, the larger firms (in terms of X_2, Total Assets) tended to have higher bond ratings. The large average size for the Baa(BBB) group was caused by the presence of several large firms including Consolidated Edison Co. of New York and Detroit Edison Co. The higher-rated firms tended to be more profitable as seen by X_6 (Net Income/ Total Assets), and had higher fixed coverage levels, X_9 (Earnings Before Interest & Taxes/Fixed Charges), than lower-rated firms. In addition, the higher-rated firms tended to have a higher ratio of Construction Expenses to Total Assets (X_{13}), while they had lower Growth Rates in Net Earnings (X_{17}) than lower-rated firms during the 1970-1975 time period.

The higher construction expenses for higher-rated firms may be due to the fact that firms in the Aa(AA) group tend to cluster in the Midwest and Southern regions of the country--areas where the demand for electrical energy was growing faster than the national average. The seeming inconsistency in the lower Growth Rates in Net Earnings (X_{17}) for higher-rated firms may be due, in part, to the accounting treatment for two separate items. First, the heavier capital expenditures

(as evidenced by variable X_{13}) experienced by higher-rated firms indicated that relatively more generating capacity was being placed into service by these firms. This would cause depreciation expenses to be greater for the higher-rated firms, thus resulting in lower reported earnings and lower growth rates. Second, an examination of variable X_{12} indicated that the Allowance for Funds Used During Construction (AFUDC) was a larger percent of net earnings for lower-rated firms. Hence, a second reason for the higher growth rates in net income for lower-rated firms may be due to the relatively large amounts of AFUDC (as a percent of net income) for lower-rated firms during this time period. In such situations, total reported earnings may be growing faster for lower-rated firms, but financial analysts rating electric utility bonds recognize the lower "quality" of earnings growth when it was due to the inclusion of larger amounts of AFUDC.

In order to test the null hypothesis that the difference in the six group means (centroids) when considered simultaneously was zero between the three bond rating groups (for both Moody's and Standard & Poor's), the F test based on Wilks lamba was employed. The null hypothesis of no difference was rejected for both Moody's and Standard & Poor's at the .001 significance level; hence, we inferred there was a significant difference between the group centroids for the three bond rating groups when the six variables were considered in a multivariate context. The next step was to examine the ability of the models to predict which bonds should be assigned to each specific bond rating category.

B. Classification Results

To test the discriminatory power of the model, every sample firm was classified into one of the three bond rating groups on the basis of the closeness of the firms' observation values to the respective group centroids. The classification matrix (Exhibit 2) shows that 70.65% (65/92) of the firms were classified correctly into their Moody's bond rating category and 76.60% (72/94) were classified according to their Standard & Poor's classification. (The total number correctly classified was determined by summing the main upper left-lower right diagonal element of the classification table.) The six-variable model did slightly better, in total, for Standard & Poor's than for Moody's suggesting that Standard & Poor's bond ratings more closely followed these six variables than did Moody's bond ratings. For both Moody's and Standard & Poor's, the model did very well for Baa(BBB)-rated firms, and did the poorest for the A-rated firms. In addition, the model did slightly better for Standard & Poor's top two categories examined, AA and A, than for Moody's (Aa and A).

While these results were impressive, they suffer an upward bias since the same firms were reclassified that were employed to develop the model. In order to validate the model, the Lachenbruch jackknife procedure [11] was employed. The essence of this procedure was to estimate the model on all but one of the observations (firms) and then classify the omitted observation. This was repeated sequentially until all observations had been classified on the basis of a model determined by the rest of the observations. The results of this validation procedure (Exhibit 3) indicated that 54.35% (50/92) were correctly

EXHIBIT 2

CLASSIFICATION RESULTS

Moody's

Actual Bond Rating	Predicted Bond Rating: Aa	A	Baa	Percent Correct
Aa	30	10	1	73.17
A	7	18	7	56.25
Baa	0	2	17	89.47

Standard & Poor's

Actual Bond Rating	Predicted Bond Rating: AA	A	BBB	Percent Correct
AA	27	5	0	84.38
A	8	30	7	66.67
BBB	0	2	15	88.24

CLASSIFICATION [illegible]
[illegible]

Moody's

Actual Bond Rating	Predicted Bond Rating: Aa	A	Baa	Percent Correct
Aa	26	13	2	63.41
A	10	12	10	37.50
Baa	1	6	12	63.16

Standard & Poor's

Actual Bond Rating	Predicted Bond Rating: AA	A	BBB	Percent Correct
AA	24	[illegible]	1	75.00
A	11	[illegible]	[illegible]	57.78
BBB	1	[illegible]	[illegible]	64.71

classified for Moody's and 64.89% (61/94) for Standard & Poor's. These overall classification results fell approximately 15 percentage points for both Moody's and Standard & Poor's bond ratings. In both cases the largest drop in correct classification occurred in the A and Baa(BBB) categories suggesting that the results were more sample sensitive for these categories than for the Aa(AA) category. We concluded that the model was reasonably effective in discriminating between the three bond rating groups, but possessed some sample specific characteristics.

C. Bonds Rated the Same by Moody's and Standard & Poor's

The model specification and classification steps reported earlier were repeated for the 69 firms that had their bonds rated the same by both Moody's and Standard & Poor's. Thus, we eliminated bonds where Moody's and Standard & Poor's differed in their ratings. By eliminating cases where the ratings differed, we eliminated differences in "rater judgment" employed by the two agencies and were able to examine the impact of specific financial variables on the classification results where the two major ratings agencies applied the same ratings. These results, reported in Exhibit 4, indicated that the six variable model correctly classified 81.16% (56/69) of those bonds where Moody's and Standard & Poor's rated the bonds the same. (Lachenbruch jackknife results are available from the authors; they indicate the same approximate dropoff in classification results reported previously.) These classification results were 5 to 10 percentage points higher than when either Moody's or Standard & Poor's were analyzed separately. As expected,

EXHIBIT 4

CLASSIFICATION RESULTS:
69 FIRMS RATED THE SAME BY MOODY'S
AND STANDARD & POOR'S

Actual Bond Rating	Predicted Bond Rating Aa(AA)	A(A)	Baa(BBB)	Percent Correct
Aa(AA)	23	5	0	82.14
A(A)	3	19	5	70.37
Baa(BBB)	0	0	14	100.00

the performance of the six variable model improved after we eliminated differences caused by "rated judgment" employed by the financial analysts at the two primary bond rating agencies.

D. Relative Importance of the Variables

When there are more than two groups, there is no single criterion for assessing the relative importance of variables in a multiple discriminant analysis model. In an attempt to obtain some insight into the relative importance of the six variables, the rank ordering (in terms of relative importance) of the six variables according to five different criteria [5] are reported in Exhibit 5. These five criteria were the univariate F ratio, the scaled weighted method, the forward stepwise and backward stepwise methods, and the conditional deletion method. Looking at the univariate F and stepwise forward results (Exhibit 5), it is apparent that variable X_9 (Earnings Before Interest & Taxes/Fixed Charges) was the most important variable, by itself, for both Moody's and Standard & Poor's bond ratings, while variable X_2 (Total Assets) tended to be the least important. However, in a multivariate framework when all variables in the model were considered simultaneously (as seen by the scaled weighted, conditional deletion and stepwise backward criteria), variable X_9 (Earnings Before Interest & Taxes/Fixed Charges) became one of the least important variables and variable X_{17} (1970-1975 Growth in Net Earnings) became the most important variable. The reason variable X_9 (Earnings Before Interest & Taxes/ Fixed Charges) was least important in a multivariate context was because of the intercorrelation (see APPENDIX B) between it and

EXHIBIT 5

VARIABLE IMPORTANCE RANKED
ACCORDING TO DIFFERENT CRITERIA

Moody's

	CRITERIA				
Variable	Univariate F Ratio	Scaled Weighted	Conditional Deletion	Stepwise Forward	Stepwise Backward
X_1	3	6	1	6	6
X_2	6	5	5	5	5
X_6	2	3	4	4	1
X_9	1	4	6	1	4
X_{13}	5	2	3	2	3
X_{17}	4	1	2	3	2

Standard & Poor's

Variable	Univariate F Ratio	Scaled Weighted	Conditional Deletion	Stepwise Forward	Stepwise Backward
X_1	3	6	1	6	3
X_2	6	2	5	4	5
X_6	4	4	4	5	2
X_9	1	5	6	1	6
X_{13}	5	3	3	3	4
X_{17}	2	1	2	2	1

the other five variables in the multiple discriminant model. Thus, in attempting to answer the question of which variable was most important, we must, of necessity, specify whether we are interested in a univariate (single variable) or a multivariate (six variable) approach. Based on a univariate approach, variable X_9 (Earnings Before Interest & Taxes/Fixed Charges) was the most important since it had the highest univariate F ratio as reported in Exhibit 4. This finding is in line with recent testimony in regulatory proceeding which indicated that the fixed coverage ratio was an important variable that financial analysts presumably look at when assigning electric utility bond ratings.

E. Classification--MDA Versus Fixed Coverage Ratio Model

Recent testimony in public utility rate cases has also suggested that unless a specific minimum value for the fixed coverage ratio was maintained, the utilities' bond rating would be downgraded. This ratio (X_9--Earnings Before Interest & Taxes/Fixed Charges) was the most important variable in a univariate sense (Exhibit 5), however in a multivariate sense it became one of the least important variables. From a classification standpoint, the importance of the fixed coverage ratio can be examined by employing it, by itself, to classify bonds into the bond rating groups (on the basis of the closeness of the individual firm's value for variable X_9 to the group means of X_9 for the respective groups). In Exhibit 6 the classification results are reported for the six-variable multiple discriminant analysis models and variable X_9 when employed by itself. (Lachenbruch jackknife results are available from the authors for the univariate model based on variable

EXHIBIT 6

CORRECT CLASSIFICATIONS: MULTIPLE DISCRIMINANT MODEL VERSUS FIXED CHARGE COVERAGE (X_9) MODEL

	CORRECT					
	Moody's		Standard & Poor's		Both	
Rating	MDA	X_9	MDA	X_9	MDA	X_9
Aa(AA)	30	15	27	14	23	11
A(A)	18	16	30	12	19	14
Baa(BBB)	17	15	15	13	14	10
Bonds Correct	65	46	72	39	56	35
Total Bonds	92	92	94	94	69	69
% Correct	70.65	50.00	76.60	41.49	81.16	50.72

X_9.) For the three different specifications examined (Moody's, Standard & Poor's, and both the same), the multiple discriminant model correctly classified 20 to 35 percent more bonds than the model based on one variable, X_9, by itself. These results provide a clear indication that the information employed by financial analysts in rating electric utility bonds is better approximated by the six variable multiple discriminant model than by the fixed coverage ratio.

Examining Moody's versus Standard & Poor's results, in Exhibit 6, indicates that variable X_9 (Earnings Before Interest & Taxes/Fixed Charges) correctly classified 50.00% for Moody's and 41.59% for Standard & Poor's. This indicated that Moody's bond ratings more closely followed one variable (i.e., fixed charge coverage) than did Standard & Poor's bond ratings.

IV. Concluding Comments

Numerous attempts have been made to develop models to predict bond ratings in recent years. By restricting our analyses to a relatively homogeneous industry, electric utilities, we developed a six variable discriminant model that correctly predicted 70% of Moody's bond ratings, 76% of Standard & Poor's and 81% for those 69 firms where both rating agencies assigned the same rating. These classification results were higher than those reported in bond rating studies employing industrial firms [9, 10, 14, 15, 18, 20]. Thus, we were able to achieve a somewhat better "fit" when a relatively homogeneous industry was selected for study. While not directly examined, our findings suggest that some of the problems with previous bond rating studies may be due to the aggregation of non-homogeneous firms in the studies.

Our analysis indicated that on a univariate basis variable X_9 (Earnings Before Interest & Taxes/Fixed Charges) was the most important variable considered by either bond rating agency; in addition, it appeared that financial analysts at Moody's tended to rely on fixed charge coverage slightly more than did Standard & Poor's analysts in determining bond ratings. However, on a multivariate basis, fixed charge coverage became substantially less important and variable X_{17} (1970-1975 Growth in Net Earnings) became the most important financial variable.

The six variable multiple discriminant analysis model substantially outperformed the univariate model based on X_9 (Earnings Before Interest & Taxes/Fixed Charges) in terms of correctly predicting the bond ratings assigned to electric utility bonds. This finding suggested that the recent attempt in some electric utility rate proceedings to specify exact fixed coverage ratios that were necessary in order to maintain (or achieve) a given bond rating, was both short-sighted and incomplete. The results of this study indicated that in the electric utility industry, as previously determined for industrial firms, many financial and certain non-financial variables (i.e., rater judgment) appear to be taken into consideration by financial analysts in determining bond ratings.

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APPENDIX A

Means, Standard Deviations,[1] and F Ratio's for Ninety-Seven Electric Utility Firms, 1975

VARIABLE	MOODY'S					STANDARD & POOR'S					TOTAL
	Aaa (5)	Aa (41)	A (32)	Baa (19)	F RATIO	AAA (3)	AA (32)	A (45)	BBB (17)	F RATIO	
X_1	1.40 (.55)	2.22 (.94)	2.50 (.88)	3.00 (.82)	5.77**	1.00 (.00)	2.16 (1.02)	2.47 (.79)	3.05 (.83)	6.75***	2.42 (.94)
X_2	1900.51 (2143.15)	1304.33 (1305.87)	1082.10 (1187.62)	1418.43 (1579.87)	.63	1073.27 (365.91)	1469.76 (1630.84)	1169.02 (1095.65)	1276.42 (1609.17)	.32	1284.10 (1364.74)
X_3	562.82 (652.60)	420.35 (453.33)	333.01 (345.41)	478.23 (637.69)	.59	297.65 (88.49)	479.09 (551.81)	352.70 (327.33)	452.70 (652.06)	.55	410.22 (471.50
X_4	.49 (.02)	.52 (.03)	.53 (.03)	.54 (.03)	4.11**	.48 (.01)	.52 (.03)	.53 (.03)	.54 (.03)	3.38*	.53 (.03)
X_5	.53 (.04)	.54 (.05)	.56 (.05)	.57 (.04)	2.06	.55 (.03)	.52 (.05)	.56 (.05)	.56 (.04)	5.64**	.55 (.05)
X_6	.04 (.01)	.04 (.01)	.04 (.01)	.03 (.01)	4.65**	.04 (.01)	.04 (.01)	.04 (.01)	.04 (.01)	3.69*	.04 (.01)
X_7	.29 (.05)	.26 (.06)	.24 (.04)	.22 (.06)	3.89*	.31 (.06)	.26 (.05)	.25 (.06)	.22 (.06)	3.27*	.25 (.06)
X_8	5.01 (.69)	4.42 (1.05)	3.97 (.69)	3.31 (.62)	9.59****	4.70 (.33)	4.56 (1.01)	3.97 (.88)	3.38 (.62)	7.42***	4.09 (.96)
X_9	4.18 (.47)	3.76 (.71)	3.40 (.44)	2.89 (.40)	12.62****	4.01 (.31)	3.86 (.69)	3.40 (.57)	2.95 (.43)	9.99****	3.49 (.67)
X_{10}	.14 (.01)	.13 (.02)	.13 (.02)	.12 (.02)	1.47	.13 (.01)	.13 (.02)	.13 (.02)	.12 (.02)	.61	.13 (.02)
X_{11}	.44 (.31)	.29 (.07)	.30 (.09)	.35 (.07)	4.48**	.55 (.39)	.28 (.06)	.31 (.08)	.36 (.08)	9.02****	.31 (.10)
X_{12}	.16 (.09)	.22 (.13)	.21 (.15)	.29 (.18)	1.74	.20 (.02)	.21 (.10)	.22 (.17)	.28 (.17)	.92	.23 (.15)
X_{13}	.15 (.03)	.12 (.04)	.11 (.04)	.10 (.04)	2.63	.16 (.03)	.12 (.04)	.11 (.04)	.10 (.04)	2.14	.11 (.04)
X_{14}	4.20 (1.30)	3.71 (1.91)	3.66 (2.22)	4.05 (3.05)	.20	5.00 (.00)	3.84 (1.80)	3.82 (2.22)	3.35 (3.08)	.51	3.78 (2.23)

X_{15}	(.09)	(.11)	(.13)	(.24)		(.10)	(.10)	(.13)	(.25)		(.15)
X_{16}	-.04 (.03)	-.03 (.04)	-.02 (.03)	-.02 (.03)	.56	-.06 (.01)	-.03 (.04)	-.03 (.03)	-.02 (.04)	1.24	-.03 (.03)
X_{17}	.05 (.01)	.06 (.03)	.08 (.04)	.09 (.05)	3.12*	.05 (.01)	.05 (.02)	.08 (.04)	.08 (.04)	4.76**	.07 (.04)
X_{18}	35.79 (43.26)	22.31 (20.27)	23.42 (29.52)	29.37 (35.24)	.56	19.03 (9.55)	25.41 (27.25)	23.65 (25.78)	27.46 (36.98)	.12	24.75 (27.88)
X_{19}	.00 (.01)	.01 (.01)	.01 (.01)	.01 (.01)	1.43	.00 (.01)	.01 (.01)	.01 (.01)	.01 (.01)	1.63	.01 (.01)

[1] In parenthesis.

[2] Millions of dollars.

*Significant at .05 level.

**Significant at .01 level.

***Significant at .001 level.

****Significant at .0001 level.

APPENDIX B

Correlation Coefficients over Nineteen Variables
for Ninety-Seven Electric Utility Firms, 1975

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}	X_{15}	X_{16}	X_{17}	X_{18}	X_{19}
X_1	1.00																		
X_2	.10	1.00																	
X_3	.09	.98	1.00																
X_4	.06	-.06	-.08	1.00															
X_5	-.04	.27	.24	.36	1.00														
X_6	-.34	-.03	-.02	-.43	-.03	1.00													
X_7	-.30	-.13	-.24	.01	-.11	.23	1.00												
X_8	-.35	-.25	-.18	-.38	-.47	.29	.21	1.00											
X_9	-.40	-.24	-.18	-.40	-.47	.44	.31	.97	1.00										
X_{10}	-.35	-.34	-.26	-.09	-.30	.06	.18	.80	.73	1.00									
X_{11}	.01	-.08	-.07	-.01	.13	-.07	-.15	-.10	-.11	-.06	1.00								
X_{12}	.23	.30	.20	.15	.24	-.05	-.08	-.72	-.61	-.77	.12	1.00							
X_{13}	-.09	-.15	-.21	.00	.06	.15	.30	-.13	-.03	-.30	.15	.36	1.00						
X_{14}	.12	-.13	-.16	.11	-.15	-.09	.26	.03	.01	-.04	-.01	-.08	.21	1.00					
X_{15}	.32	-.02	-.06	.11	-.01	-.58	-.15	-.15	-.25	-.06	-.01	.07	-.05	-.08	1.00				
X_{16}	-.10	.04	.08	-.14	.00	.07	-.01	.43	.38	.52	.00	-.49	-.32	-.18	-.14	1.00			
X_{17}	-.07	.16	.10	.00	.48	.38	.15	-.36	-.26	-.29	.08	.38	.20	-.06	-.37	.13	1.00		
X_{18}	.00	.92	.90	.00	.27	-.04	-.04	-.17	-.15	-.17	-.09	.22	-.19	-.20	-.07	.19	.23	1.00	
X_{19}	.09	.29	.35	-.04	.24	-.02	-.39	-.20	-.21	-.11	.00	.17	-.18	-.42	.11	.02	.18	.34	1.00

APPENDIX C

A Four-Group Multiple Discriminant Model

Because of the small sample size of the Aaa group for Moody's (5) and the AAA group for Standard & Poor's (3), and the necessity to calculate separate dispersion matrices (because of the inequality of the dispersion matrices), a four-group multiple discriminant model could not be estimated by the normal procedure. Two alternative approaches might be employed in attempting to develop a four-group model. First, we could assume that the dispersion matrices for all four groups were equal so that a pooled dispersion matrix could be estimated over the 97 bonds. This approach would allow a linear four-group model to be estimated in the usual manner, but does not take account of the inequality in the dispersion matrices for the Aa(AA), A, and Baa(BBB) groups. This inequality in the group dispersion matrices indicates that an assumption of equal dispersion matrices is not valid; hence, quadratic as opposed to linear classification procedures should be employed.

A second approach to the problem involves the estimation of the Aaa(AAA) group dispersion matrix so that quadratic classification procedures can still be employed. This subject has not been examined widely and, we believe, requires some elaboration. The crux of the problem is how to obtain a "reasonable" estimate of the dispersion matrix for the Aaa(AAA) group that cannot be estimated because of the small sample size. One possible approach would be to estimate this unobservable dispersion matrix as being the same (or equal to)

the dispersion matrix for the next closest observable group. Thus, following this procedure we would estimate the Aaa(AAA) dispersion matrix as being equal to the dispersion matrix for the Aa(AA) group. Once this assumption is made, we have separate estimates of all four dispersion matrices (even though two of them are equal)--hence the quadratic classification can be completed.

Four-group classification results from employing this latter procedure are reported in EXHIBIT C1 for the 97 cases for Moody's and Standard & Poor's, and the 72 cases where both agencies rated the bonds the same. For all three models the classification results did not change for the A and Baa(BBB) groups. However, the number of Aa(AA)-rated bonds classified correctly decreases for all of the models because some of the bonds formally estimated as Aa(AA), were now placed in the Aaa (AAA) group. The overall (percentage) classifitory ability of the multiple discriminant models decreased in all three cases from the three group results; in addition, the Moody's four-group model also suffered an absolute decrease of one less bond being correctly classified than for the three-group model. While this procedure does allow estimation of a four-group quadratic discriminant model, it suffers one drawback--the reasonableness of the assumption that the unobservable Aaa(AAA) group dispersion matric being equal to that of the Aa(AA) group cannot be ascertained.

EXHIBIT C1

Classification Results for the Four-Group Model

MOODY'S				STANDARD & POOR'S				BOTH THE SAME			
Rating	Actual	Predicted	Percent Correct	Rating	Actual	Predicted	Percent Correct	Rating	Actual	Predicted	Percent Correct
Aaa	5	4	80.00	AAA	3	2	66.67	Aaa(AAA)	3	2	66.67
Aa	41	25	60.98	AA	32	25	78.12	Aa(AA)	28	21	75.00
A	32	18	56.25	A	45	30	66.67	A(A)	27	19	70.37
Baa	19	17	89.47	BBB	17	15	88.24	Baa(BBB)	14	14	100.00
TOTAL	97	64	65.98	TOTAL	97	72	74.23	TOTAL	72	56	77.78